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Fused Attentive Generative Adversarial Network based Personalized English Learning Material Recommendation System utilizing Knowledge Graph

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Abstract: - The information era has arrived swiftly in the world. Because it is the universal language, English influences how information is transmitted and exchanged throughout the world. Learning English is like having a valuable instrument for learning priceless knowledge. For this reason, it is imperative that English instruction be improved. The Fused Attentive Generative Adversarial Network based Personalized English Learning Material Recommendation System utilizing Knowledge Graph. Initially, input data are collected, given to preprocessing method. In preprocessing remove data redundancy using Generalized Correntropy Sparse Gauss–Hermite Quadrature Filter (GCSG-HQF). In pre-processed output fed to Recommendation System. Here, FAGAN is used to recommend English Learning Material. In general, FAGAN classifier does not express any optimization adaption approaches for determining optimum parameters to assure the Knowledge Graph. Here Clouded Leopard Optimization Algorithm utilized to optimize FAGAN classifier, for Personalized English Learning Material Recommendation System. In Clouded Leopard Optimization Algorithm utilized to optimise weight parameter of the FAGAN. With the use of performance metrics likes accuracy, precision, sensitivity, specificity, F1-score, ROC, computational time are analyzed. The proposed FAGAN-ELMRS-CLOA method attains 30.58%, 28.73% and 35.62%, higher accuracy, 20.48%, 24.73%, 29.32% higher computational time and 30.98%, 26.66% and 21.32% higher ROC analysed with existing models such as personalized English learning material recommendation system depend on knowledge graph (CNN-ELMRS-KG), semantic method for document classification utilizing deep neural networks with multimedia knowledge graph (DNN- ELMRS-MKG), and personalized recommendation of English learning depend on knowledge graph with graph convolutional network (PR- ELMRS-GCN) respectively.

Keywords: Clouded Leopard Optimization, Fused Attentive Generative Adversarial Network, GCSG-HQF.

I. INTRODUCTION

The world has hurriedly entered the information age due to rapid growth of the digital economy, AI [1]. Because it is the universal language, English influences how information is transmitted and exchanged throughout the world. [2]. Without a doubt, the ability to communicate in English is currently crucial for quickly gaining knowledge of a variety of cutting-edge technologies and professional subjects [3]. English instruction is offered in educational settings ranging from primary schools to colleges and institutions [4]. English is now a valuable language for individuals to learn and obtain knowledge from a variety of media sources, rather than just a tool for everyday communication amongst people [5]. As a result, the effectiveness and calibre of English instruction are extremely important [6]. The time and space constraints of traditional English classroom instruction prevent teachers from offering students enough language application opportunities [7]. Despite the abundance of learning resources available to students on online platforms and mobile applications, there are two typical issues that frequently accompany online English learning [8] they could become disinterested in what they are studying, become sidetracked, or even feel confused and perplexed by what they have learned; [9] Students typically have varying levels of learning and comprehension; hierarchies exist for learning levels even within a class, and students' needs for knowledge acquisition vary [10]. The majority of the knowledge content on existing online learning platforms is divided based on students' grades. This has led to problems like inadequate learning materials for good students, average and poor students never learn [11].Thus, given these two concerns, it is important to carefully analyse how to achieve personalised learning resource recommendations depend on unique necessities of learners and features of their English knowledge [12]. In reference to the first issue raised above, examined features of English as linguistic instrument, knowledge features using an English course of particular grade as example. It then sorted out the structure of knowledge system, created a knowledge graph for course to represent knowledge points [13]. Regarding the second issue, this work examined the learning behaviour trajectories of the students in the grade, their user profiles, and the unique circumstances of online teaching platforms [14]. It built personalised English learning material recommendation scheme, investigated few important points like system recommendation flow, user portrait, recommendation process, and labelled linked knowledge points of learning data online learning platforms with aid of a knowledge graph [15].

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When faced with such vast amounts of learning material, students who do not have the professional direction of professors frequently become confused; they may lose interest in what they are studying, become side tracked, or even feel perplexed and confused by what they have learned. Pupils typically have varying degrees of learning and comprehension; hierarchies exist even within classes, and students have distinct needs when it comes to acquiring knowledge.

This research analysed the issue of students being lost in the vast amount of online learning materials by combining their English skills with other factors. It then developed an accurate and efficient personalised approach for recommending English learning materials. The suggested system's operation and deployment can increase the effectiveness of learning English by saving students a great deal of time spent on data search and inquiry.

Major contributions of this manuscript brief as below:

- The FAGAN-ELMRS-CLOA system introduces a novel approach to Personalized English Learning Material Recommendation, leveraging Knowledge Graphs for efficient English learning material suggestions.
- Through the application of GCSG-HQF, data redundancy is effectively eliminated in the personalized recommendation system.
- The recommendation of English Learning Material is facilitated through the application of Fused Attentive Generative Adversarial Networks.

Remaining part of this manuscript arranged as below: segment 2 examines literature review, proposed method defined in segment 3, results with discussion is established in segment 4, conclusion presented in segment 5.

II. METHODOLOGY

Several investigation works were presented in literature connected to English Learning Assessment System depend on Knowledge Graph using DL; some of current investigations were assessed in this part.

Huang and Zhu [16], have presented personalized ELMRS depend on KG. Here, examines the issues with both online and traditional classroom English instruction, and it offers solutions for keeping students engaged in the process, increasing their proficiency, and meeting their individual needs. In particular, a knowledge graph was created by characterising the pertinent data with knowledge points related to English instruction. Subsequently, the pertinent knowledge points were marked in learning platforms' online learning data. Following that, a user picture was produced through data analysis on everyday learning behaviours. Ultimately, content-based suggestion combined with collaborative filtering was used to provide students with English learning materials that tailored to their individual needs. It provides high accuracy and low precision.

Rinaldi et al. [17], have presented semantic method for document classification utilizing DNN-MKG. Here, propose an innovative approach that offers a framework for classifying multimedia online content utilizing semantic investigation, ontologies, metrics depend on multimedia semantic comparison. Extra data was taken from over-all knowledge repository. The semantic knowledge base was based on research described in Russo. Based on combined textual and visual examination of the source material, semantic topic detection technique was presented.It provides high F1-scoreand low Mean absolute error.

Sun et al. [18], have presented PR of English learning depend on knowledge graph with GCN. Here,provide a strategy depend on knowledge graphs, GCN for customising the suggestion of English learning. Create a knowledge graph by first classifying large Junior High School English activities using knowledge points. It attains students by in-depth personalized services making personalized learning path. As a result, it offers greater Sensitivity and higherF1-score.

Liu et al. [19], have presented dynamic knowledge graph reasoning depend on DRL. Here, depend on DRLdynamic knowledge graph reasoning framework was put forth that can travel the graph and identify the likely target response conditioned on the input question. To accomplish dynamic reasoning, the judgement condition was set, embedding method was selected as trained method for initialization. As a result, it offers greater accuracy and a lower precision.

Rossi et al. [20], have presented explaining link prediction scheme depend on knowledge graph embedding. Here, posit innovative Kelpie explain ability paradigm. Any embedding-based LP model can use Kelpie, regardless of its architecture; explains forecasts by figuring out combinations of training facts made them possible. Kelpie was able to derive two types of explanations that are deemed sufficient and necessary, respectively. Give a detailed explanation of Kelpie's architecture and implementation, and conduct in-depth experimentation to evaluate its effectiveness. As a result, it offers greater specificity and lower computational time.

Lin et al. [21], have presented fusing topology contexts withlogical rules in language methods for knowledge graph completion. Here, suggest combining logical rules with topological contexts in LMs for KGC using the FTL-LM architecture. Use an indirect approach since achieving direct fusion is unfeasible. To create topology pathways, a heterogeneous random-walk technique was specifically presented. Next, the topological paths transformation yields the reasoning paths. As a result, it offers greater precision and lower computational time.

Koloski et al. [22], have presented Knowledge graph informed fake news classification through heterogeneous depiction ensembles. Here, examine potential applications of various document representations for effective fake news identification, from straightforward symbolic bag-of-words representations to contextual, neural language method-depend ones. Moreover, knowledge graph-depend document depictions attain state-of-the-art presentation paired by contextual representations that already exist. It offers greater F1-scoreand lower RoC.

III. PROPOSED METHODOLOGY

FAGAN-ELMRS-CLOA is discussed in this section. This section presents the English learning material recommendation system Using Fused attentive Generative Adversarial Network. The block diagram of FAGAN-ELMRS-CLOA is represented by Figure 1. Thus, the detailed description about FAGAN-ELMRS-CLOA is given below,

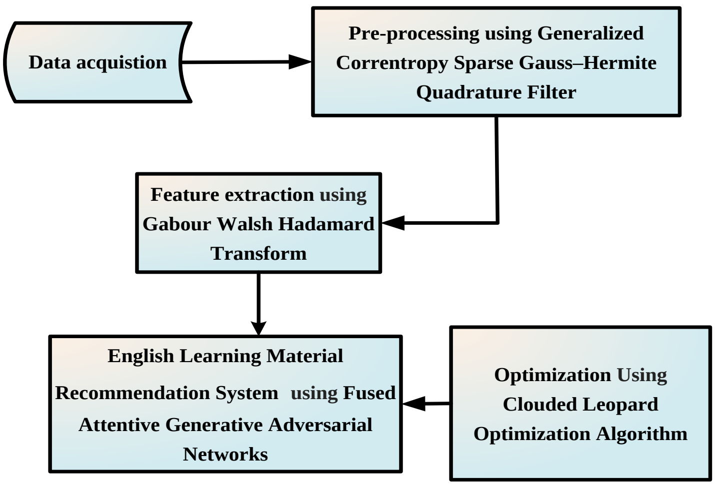

Figure 1: Block diagram of proposed FAGAN-ELMRS-CLOA methodology

A. Construction of knowledge graph

The proposed technique involves constructing knowledge graph based on the targeted grade's curriculum, utilizing technologies related to knowledge graphs and networks. The knowledge graph, consisting of "Entity-Relation-Entity" triplets and entities with attributes, serves to visually represent the subject's structure and interconnections between knowledge nodes. The advantages include its ability to reflect system structure, visualize knowledge, and adapt to system expansion. Constructing such a knowledge graph aids students in expanding and transferring knowledge, fostering independent learning. It also addresses issues like information overload in online resources through personalized recommendations. For multimedia resources, user labelling mechanisms are suggested to manually assign refined characteristics, overcoming challenges in machine comprehension of image, video, and audio contents.

B. Data acquisition

Data collection sources on teaching platform [26] are mostly collected of unstructured data (likes images, audios, texts, videos), few semi-structured data (likes JSON, XML, Encyclopedia); such dual types of data can't be known by computers, necessity to altered into structured data to execute succeeding process intentions.

C. Pre-processing using Generalized Correntropy Sparse Gauss–Hermite Quadrature Filter

In this step, GCSG-HQF [23] is used for remove data redundancy. A method of numerical integration that works especially well for functions with Gaussian distributions is called Gauss–Hermite quadrature. This could help to accurately capture and depict the data's underlying structure in the context of removing data redundancy. All-around correntropy the generalised correntropy is used by GCSG-HQF to increase robustness even more when there are outliers present. A fresh measurement update is needed to incorporate the generalised correntropy into the GCSG-HQF is shown in equation (1),

$$\left[x_q - z\left(\hat{y}_q\right) + Z_q Y_{q|q-1}\ \right] = \begin{bmatrix} J \\ Z_q \end{bmatrix} Y_q + U_q \tag{1}$$

Where $Z_q Y_{q|q-1}$ is the identity matrix, and Sparse representations inherently reduce dimensionality by focusing on a subset of features. This can contribute to the removal of redundant information, especially in high-dimensional is shown in equation (2),

$$Uq = \begin{bmatrix} -\left(Yq - \hat{y}_{q|q-1}\right) \\ s_q \end{bmatrix} \tag{2}$$

In Uq has a second-order statistical characteristic $Yq - \hat{y}_{q|q-1}$ given by Correntropy, with its ability to capture nonlinear relationships, might be effective in identifying nonlinear redundancy. Applying Cholesky decomposition to $L_{yx,q|q-1}$ remove data redundancy and linear regression model $L_{q|q-1}$ can be developed in equation (3),

$$\Phi_q = \Theta_q y_q + t_q \tag{3}$$

To find y_q data redundancy through iteration to minimize the loss function corresponding to the clustering results. Finally GCSG–HQF is used to remove data redundancy. Then, the pre-processed output is fed into Fused Attentive Generative Adversarial Networks to recommend the English Learning Material.

D. Fused Attentive Generative Adversarial Networks

In this section, English learning material recommendation using FAGAN [24] is discussed. By enabling the model to concentrate on pertinent details and structures during the generation process, FAGAN can result in better English learning recommendation. The model may take into account both local and global settings thanks to the fusion of attention, which facilitates more efficient learning and the production of coherent outputs. The operation can be defined as in equation (4),

$$J^{PS} = g\left(J^{QS}\right) \tag{4}$$

Where J^{PS} are respectively and size J^{QS} means down-sampling process makes LR counterpart from HR image is shown in equation (5),

$$G_{e,1} = \left[D_{3\times3}\left(G_{e-1}\right), G_{e,1}\right] \tag{5}$$

Where G_{e-1} denotes S measure feature extractor. The proposed S measure feature extractor consists of three convolution layers by $D_{3\times3}$ kernel size, ReLU intermediate activation layer. After transposing output of G_{e-1}, multiplying output matrix through normalizing by soft-max to get G_c attention map. It is given in equation (6),

$$\alpha_{i,j} = \frac{\exp\left(r_{ji}\right)}{\sum_{j=1}^{M} \exp\left(r_{j,i}\right)} \tag{6}$$

Where $\alpha_{i,j}$ specifies extent to method attends to $j-th$ location synthesizing $j-th$ area. Here, M denotes number of channels, g signifies feature locations of features from preceding hidden layer. Output of attention layer is O, shown in equation (7),

$$wi = u\left(\sum_{j=1}^{M} \alpha_{i,j} z\left(y_j\right), z\left(y_j\right)\right) = O_u y_j \tag{7}$$

The learnt weight matrices, implemented as 1 × 1 convolution, are in the formulation above. Additionally, add input feature map back to attention layer's output after multiplying it by a scale parameter. Based on the above considerations, the overall objective of generating data adaptation boundary enhancement recommends the English Learning Material is discussed in equation (8),

$$x_{RB} = \delta w_j + y_j \tag{8}$$

Where δ denotes learnable scalar with initialized to 0. Presenting learnable δ make network depend on information of local neighbourhood, progressively learn to allocate further weight to non-local information.Finally, FAGAN for recommend the English Learning Material. Due to its convenience, pertinence, AI-depend optimization approach is taken into account in FAGAN classifier. The CLOA is employed to enhance FAGAN optimum parameter $G and \alpha$. The CLOA is employed for tuning weight, bias parameter of FAGAN.

E. Optimization using Clouded Leopard Optimization Algorithm

The weights parameter $G\ and\ \alpha$ of proposed FAGAN is optimized using the proposed Clouded Leopard Optimization Algorithm (CLOA) [25].CLOA is designed to efficiently search the solution space and find global optima, making it suitable for optimization problems with complex and multi-modal landscapes. CLOA balances exploration and exploitation effectively, allowing it to explore diverse regions of the solution space while exploiting promising areas, leading to a robust and well-balanced optimization process.

1) Stepwise process of CLOA26

The stepwise process defined to attain optimal values of FAGAN utilizing POA. Initially, CLOA creates uniformly distributed population for improving optimal parameters of FAGAN parameters. Optimal solution is promoted utilizing POA method then equivalent flowchart given in Figure 2. The procedure of complete stage is follows,

Step 1: Initialization

Every clouded leopard in the CLOA design symbolises a potential problem-solving candidate as well as a member of the population. The values of choice factors displayed by clouded leopard's position inside search field. Therefore, some clouded leopard represented mathematically as vector, with its components serving as decision variables. The location of clouded leopards at search space is initialised at random at the start of the algorithm using equation (9),

$$\begin{aligned} Y_j = v_i + s_{j,i}.(v_i - v_i),\ j = 1,2,\ldots,M, \\ i = 1,2,\ldots,n \end{aligned} \tag{9}$$

Where Y_j denotes ith clouded leopard, v_i signifies $j-th$ dimension, M denotes number of clouded leopards, M signifies decision variables, $s_{j,i}$ are randomly selected numbers at interval [0, 1], v_i denotes lower bound, $_{j,i}$ signifies upper bound of $j-th$ decision variable, respectively, exact notation for scalar multiplication.

Step 2: Random generation

After initialization, input parameters are made at randomly. Based on their specific hyper parameter conditions, the optimal Progressive value is selected.

Step 3: Fitness function

It creates random solution from initialized values. It calculated using equation (10),

$$FitnessFunction = optimize(G and \alpha) \tag{10}$$

Step 4: Exploration

At night, the clouded leopard emerges from its hiding spot and goes hunting. The clouded leopard's nocturnal activity prompts them to shift places as they hunt. This clouded leopard approach uses metaheuristic algorithms to represent the ideas of exploration and global search, enabling population members to precisely and globally scan various regions of the search space. If novel location has better value for objective function, it substitutes preceding location of corresponding clouded leopard, given in equation (11),

$$Y_j = \begin{cases} Y_j^{O1} & G_j^{O1} \\ Y_j & else \end{cases} \tag{11}$$

Where Y_j denotes novel location suggested for ith clouded leopard depend on first phase of G_j^{O1} is its $j-th$ dimension Y_j^{O1} denotes objective function value, Y denotes random numbers at interval [0, 1].

Step 5: Exploitation phase for optimizing $G\,and\,\alpha$

After hunting and devouring their victim, clouded leopards go to woods to relax and digest their food. They consequently rest on trees for the majority of the day. The clouded leopards' actions cause a shift in their location close to where they are found in equation 12).

$$Y_j = \begin{cases} Y_j^{O_2} & G_j^{O_2} < G_{j;} \\ Y_j & \alpha \end{cases} \tag{12}$$

Where $Y_j^{O_2}$ denotes novel location suggested for ith clouded leopard depend on second phase of $G_j^{O_2}$ dimension, G denotes objective function value, α denotes selected numbers from interval at [0, 1].

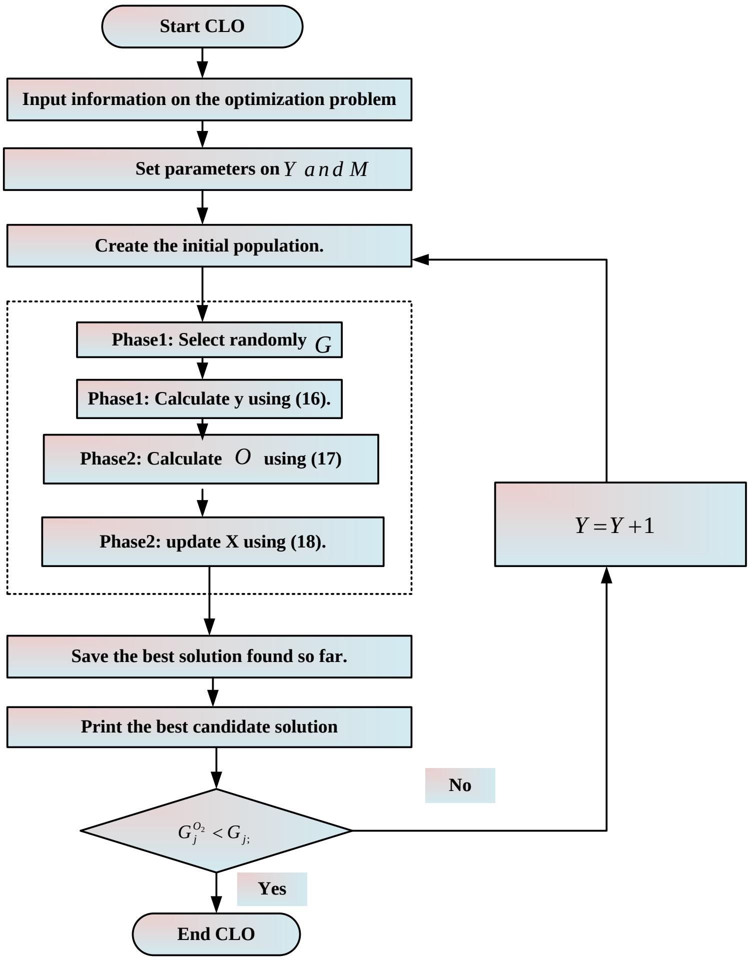

Figure 2: Flowchart of CLO for enhancing FAGAN parameter

Step 6: Termination condition

The weight parameters $G\,and\,\alpha$ from Fused Attentive Generative Adversarial Networks are optimized by support of CLOA process, iteratively reiteration step 3 until halting conditions $Y = Y + 1$ met**.** Then finally FAGAN recommend the English Learning Materialwith better accuracy through lower computational time error.

IV. RESULT WITH DISCUSSION

Experimental result of suggested method is discussed. The proposed technique is executed in python. Utilising a workstation equipped with an 11-GEN CPU and an Intel core i7 with 8 GB RAM. Obtained outcomes of the proposed FAGAN-ELMRS-CLOA technique is analyzed with existing technique such as CNN-ELMRS-KG, DNN- ELMRS-MKG, PR- ELMRS-GCN respectively.

A. Performance measures

Performance of proposed technique is calculated utilized following performance metrics. The performance evaluation matrices such as precision, Sensitivity, F-scores, specificity, accuracy, RoC and computational time have been taken into consideration while conducting the proposed research. To measure performance matrix, True Negative, True Positive, False Negative, False Positive values are needed.

1) Accuracy

It is a metric utilized to scale overall correctness of English learning, calculated as ratio of correctly categorized the instances to total instances in dataset. It is calculated using equation (13),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{13}$$

2) Precision

It is a metric of classification models, evaluates the accuracy of positive forecasts made by method. It intended as ratio of true positive forecasts to sum of true positive, false positive forecasts is shown in equation (14),

$$\mathrm{Pr}ecision = \frac{TP}{(TP + FP)} \tag{14}$$

3) Sensitivity

Sensitivity is a metric for the efficiency of English Learning Material recommendations. It is also known as the rate of recognition. It specifies the percentage of positive tuples that the prediction model successfully classified. It is given in equation (15),

$$sensitivity = \frac{TP_a}{(TP_a + FN_T)} \tag{15}$$

4) Specificity

It is the proportion of English Learning Material that recommends English learning. The specificity is described by true negative rate. It is shown in equation (16),

$$\mathrm{Specificity} = \frac{TN}{(FP + TN)} \tag{16}$$

5) F1-score

It is a metric commonly used in classification models combines both precision, recall into single value, attaining more balanced assessment of method's performance is calculated using Equation (17),

$$F1 - Score = 2 \times \frac{recall \times precision}{recall + precision} \tag{17}$$

6) RoC

RoC provides information about English Learning Material recommendations. It is scaled in equation (18),

$$RoC = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + TP} \right) \tag{18}$$

B. Performance analysis

Figure 3 to 9 displays simulation results of FAGAN-ELMRS-CLOA technique. Then FAGAN-ELMRS-CLOAmethod is analyzed with existing CNN-ELMRS-KG, DNN- ELMRS-MKG and PR-ELMRS-GCN methods respectively.

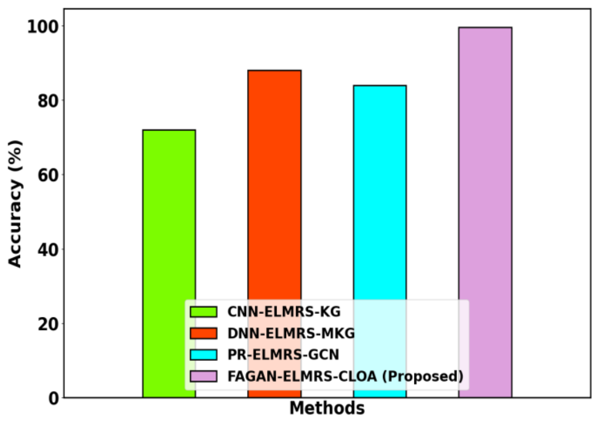

Fig 3: Accuracy analysis

Figure 3 depicts accuracy analysis. Accuracy is evaluating the performance of an FAGAN. It measures the ratio to total number of instances in dataset. The FAGAN-ELMRS-CLOA method attains 32.58%, 26.73%, 24.22%, greater accuracy analysed with existing techniques such as CNN-ELMRS-KG, DNN- ELMRS-MKG and PR-ELMRS-GCN respectively.

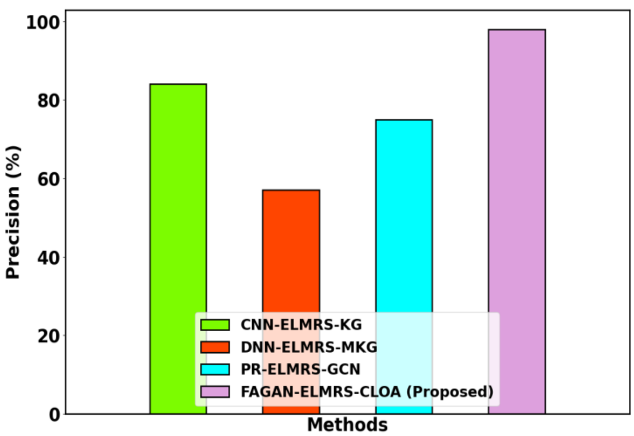

Fig 4: Precision analysis

Figure 4portrays precision analysis. Precision is quality of being exact and accurate. It is the degree to which a measurement or calculation is repeatable and consistent. The proposed FAGAN-ELMRS-CLOA method attains 24.58%, 22.73%, 29.62%, greater precision analysed with existing techniques such as CNN-ELMRS-KG, DNN- ELMRS-MKG and PR-ELMRS-GCN respectively.

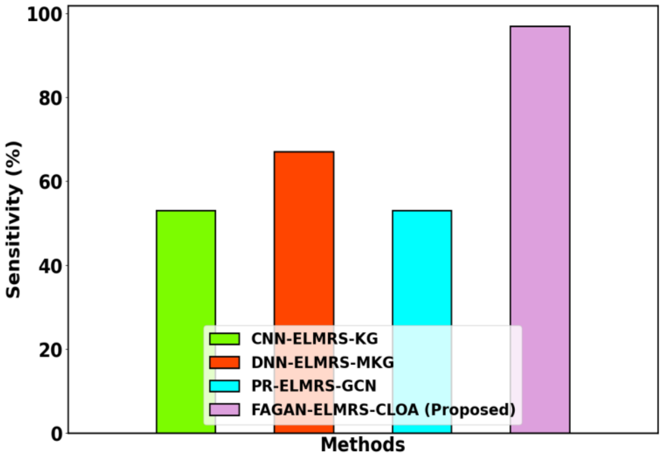

Fig 5: Sentivity analysis

Figure 5 depicts Sentivity analysis. Sentivity is a measure of a selector targets, scales ratio to total number of instances. The FAGAN-ELMRS-CLOA method attains 32.58%, 26.73%, 24.22%, higher Sentivity analysed with existing techniques such as CNN-ELMRS-KG, DNN- ELMRS-MKG and PR-ELMRS-GCN respectively.

Figure 6 depicts Specificity analysis. Specificity is a measure of a selector targets, scales the ratio to total number of instances. The FAGAN-ELMRS-CLOA method attains 32.58%, 26.73%, 24.22%, higher specificity analysed with existing techniques such as CNN-ELMRS-KG, DNN- ELMRS-MKG and PR-ELMRS-GCN respectively.

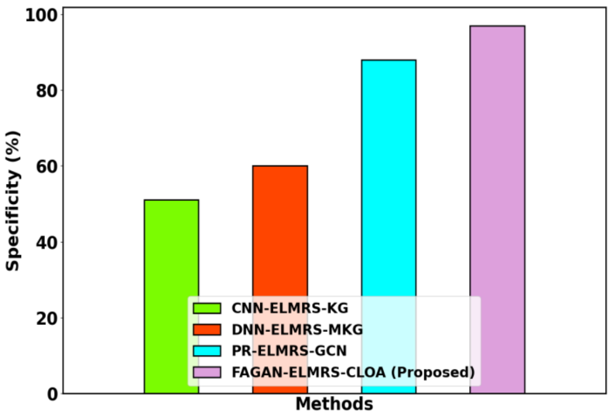

Fig 6: Specificity analysis

Figure 7 depicts F1-score analysis. It is generally utilized as metric to evaluate performance of FAGAN technique. The proposed FAGAN-ELMRS-CLOA method attains 26.58%, 20.73% and 19.62%, greater F1-score analysed with existing techniques such as CNN-ELMRS-KG, DNN- ELMRS-MKG and PR-ELMRS-GCN respectively.

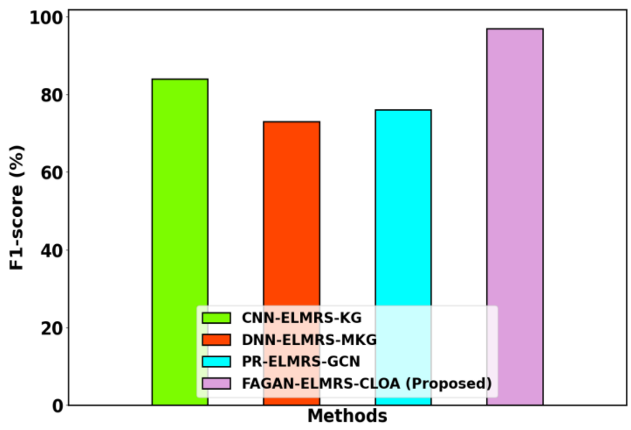

Fig 7: F1-Score analysis

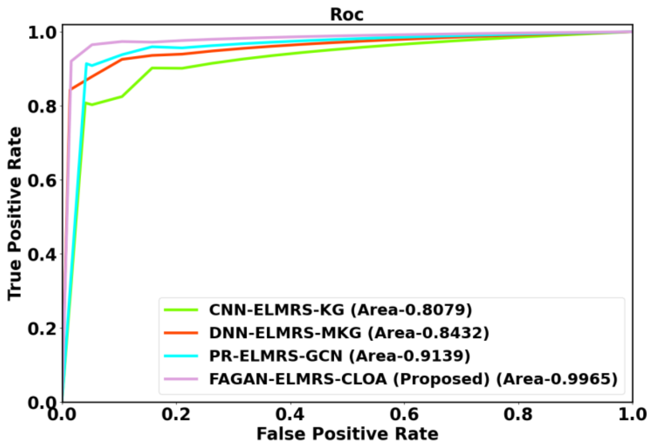

Fig 8: RoC analysis

Figure 8 portrays RoC analysis. It is graphical representation utilized to evaluate performance methods across different discrimination thresholds. The proposed FAGAN-ELMRS-CLOA technique attains 32.30%, 30.92% and 27.37% higher RoC analysed with existing methods such as CNN-ELMRS-KG, DNN- ELMRS-MKG and PR-ELMRS-GCN respectively.

Figure 9 depicts computational time analysis. It refers to the duration taken by a computer or a computational system to complete a specific task or process. The FAGAN-ELMRS-CLOA technique achieves 280s, 250s, and 240s lower computational time analysed with existing techniques likes CNN-ELMRS-KG, DNN- ELMRS-MKG and PR-ELMRS-GCN methods.

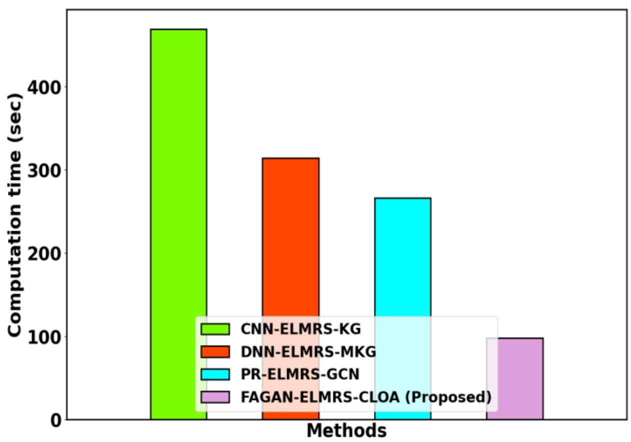

Fig 9: Computational time analysis

C. Discussion

In this study, highlight the importance of learning English as the universal language of access to important information in the digital era. Goal of the investigation is to make personalised ELMRS that is built on Fused Attentive Generative Adversarial Network (FAGAN) and coupled with a knowledge graph. Combining with features of English knowledge, evaluated issue these students often get lost massive online learning materials, constructed effectual, precise personalized ELMRS. The proposed method utilized knowledge points of English course to describe data, make knowledge graph, applicable technologies of proposed method presented. Learners' behaviour data were taken into account to create a complete user portrait, exact knowledge graph structure, user label data was combined by mixed recommendation technology to make recommendations to achieve personalized, customized recommendations. The operation, execution of FAGAN-ELMRS-CLOA scheme support learners save more time spent data search, query and develop efficacy of English learning.

V. CONCLUSION

In this section, FAGAN-ELMRS-CLOA was successfully implemented. The proposed FAGAN-ELMRS-CLOA method attains 30.58%, 28.73% and 25.62%, higher precision, 20.48%, 24.73%, 29.32% higher specificity and 30.98%, 26.66% and 21.32% higher F-score, 26.78%, 34.47%, and 22.86% better recall analysed, with existing techniques like CNN-ELMRS-KG, DNN- ELMRS-MKG, and PR-ELMRS-GCN respectively. The operation, execution of proposed method support learners save more time spent on data search, query, develop efficacy of English learning.

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